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ABSTRACT

We study the role of oil prices in forecasting Russian recession periods with probit models. Our findings suggest that fluctuations in nominal oil prices are useful predictors of the Russian business cycle, even when controlling for a number of classic recession predictors. However, in line with international findings, the term spread turns out to be the most powerful predictor of future recessions. Overall, the best in-sample fit is found using a model including the term spread and the oil price variable as predictors. The pseudo out-of-sample forecasts confirm the findings.

1. Introduction

Russia is the second largest producer of natural gas and the third largest producer of oil in the world, with over 106 billion barrels of oil reserves at the end of 2017. Furthermore, it is the largest exporter of oil in the world (BP, 2018). Exports of mineral products (consisting mainly of oil and natural gas) accounted for 59.2% of total Russian exports in 2016 (Rosstat, 2017). Given these figures, it is undeniable that changes in oil and gas prices have a large impact on the economic fluctuations in Russia. In this article, we will analyze the impact of oil price changes on Russian business cycle fluctuations by means of probit models.

The role of oil prices as a source of business cycle fluctuations has been a topic of wide interest, and was sparked by the two oil crises in the 1970s. Early contributions in the literature include Hamilton (1983), who found statistical evidence of increases in oil prices leading recessions in the U.S., and since then, the topic has received wide attention (see, e.g., Serletis and Elder, 2011 and references therein). Extensions to the literature have suggested that the relationship may be asymmetric (Mork, 1989; Hamilton, 2011), as well as dependent on whether the shock in oil price is demand or supply driven (Brown and Yucel, 2002; Kilian, 2009). Furthermore, the effects of oil price shocks vary between oil producing and importing countries (see, e.g., Mork et al., 1994), where increases of oil prices have found to have significant positive effects on output in oil exporting countries (see, e.g., Berument et al., 2010).

In the literature on business cycle fluctuations, binary dependent variable models, such as probit and logit models, have been a standard tool in modelling the probability of recessions since the seminal paper of Estrella and Hardouvelis (1991). The findings based on these models have identified the term spread and stock market returns as useful predictors of U.S. recessions (see, e.g.,

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¹ Disclaimer: The opinions expressed in this article are the author's own and do not reflect the views of the Finnish Ministry of Finance.



Fig. 1. Russian recession periods and the Brent oil price 1997Q1–2017Q4.

Estrella and Mishkin, 1998; Chauvet and Potter, 2005; Nyberg, 2010; Ng, 2012). Later research has suggested that also sentiment (Christiansen et al., 2014) and credit (Pönkä, 2017) variables have predictive ability for future recession periods.

We contribute to the literature by studying oil price – business cycle relationship in Russia. Although the Russian economy is in many ways dependent on oil production, making it an ideal candidate for research on the topic, the relationship between oil prices fluctuations and recession periods in Russia has not been studied widely in a formal econometric setting. The existing literature has examined the relationship between oil prices and real GDP growth in Russia in a structural vector autoregressive (SVAR) framework (see, e.g., Rautava, 2004; Ji et al., 2015; Alekhina and Yoshino, 2018). This differs from our approach, since we are more explicitly interested in the role of oil price fluctuations as a leading indicator of recessions and expansions. Nevertheless, the findings of the SVAR literature have documented that real GDP in Russia exhibits a positive response to oil price increases.

Further motivation for analysing the relationship is given in Fig. 1, indicating that three latest recession periods in Russia (as defined in Section 3.1) have coincided with decreases in oil prices. Obviously, there are also other contributing factors to these recessions, discussed e.g., in Smirnov et al. (2017), but the relationship implied by the figure calls for a formal investigation between oil prices and Russian recession periods.

The findings of our study suggest that changes in oil prices have predictive ability on future recession periods. Furthermore, models combining the oil price variable with classic recession predictors improve the in-sample performance, as measured with the area under the receiver operating characteristic curve (AUC). However, our findings point out that the term spread is the most powerful predictor of future recessions in Russia, which is in line with findings from previous literature on other countries (see, e.g., Estrella and Mishkin, 1998; Nyberg, 2010) that have highlighted the role of the term spread as a leading indicator. The best in-sample fit is obtained with a model using the term spread and the oil price variable as predictors. The out-of-sample findings are in line with the in-sample results, as models including the term spread and change in oil prices yield the highest AUCs.

The rest of this paper is organised in the following way. In Section 2, we describe the employed model and goodness-of-fit measures. In Section 3, we discuss the data, including the business cycle chronology and the explanatory variables. In Section 4, we present the empirical findings of the study. Finally, Section 5 concludes.

2. Empirical approach

In this section we present the econometric framework and discuss goodness-of-fit measures related to the probit model.

2.1. The probit model

We are interested in understanding the drivers of business cycle fluctuations in Russia, and especially on the role of oil price changes as an explanatory variable. Therefore, throughout the analysis, the dependent variable is the status of the Russian business cycle. In practice, this variable is a binary indicator given by:

$$y_t = \begin{cases} 1, & \text{if the economy is in a recession,} \\ 0, & \text{if the economy is in an expansion.} \end{cases} \quad (1)$$

As the methodology we employ probit models using lagged potential predictors, such as changes in oil prices, as explanatory

variables. To determine the conditional probability of a recession (p_t), a univariate probit model is specified as

$$p_t = P_{t-1}(y_t = 1) = \Phi(\pi_t), \quad (2)$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and π_t is a linear function of the variables in the information set Ω_{t-1} . In a standard static probit model, π_t is specified as

$$\pi_t = \omega + \mathbf{x}'_{t-k}\boldsymbol{\beta}, \quad (3)$$

where ω is a constant term and \mathbf{x}_{t-k} includes the k :th lagged values of the explanatory variables. We estimate the parameters of the model using maximum likelihood and compute robust standard errors, similarly to Kauppi and Saikkonen (2008).

We also consider an extension to the conventional static probit model. More explicitly, we employ the first-order autoregressive probit model of Kauppi and Saikkonen (2008)

$$\pi_t = \omega + \alpha_1 \pi_{t-1} + \mathbf{x}'_{t-k}\boldsymbol{\beta}. \quad (4)$$

An autoregressive structure is introduced into the model by including the lagged value of the linear function π_t . The autoregressive specification of the probit model has been found by Nyberg (2010, 2014) to outperform static models in predicting U.S. and German recessions.

2.2. Goodness-of-fit measures

There are several possible measures for evaluating the goodness-of-fit of binary dependent variable models. The most obvious one is the percentage of correct predictions, typically referred to as the success ratio (SR). Formally, a signal forecast for the state of the economy y_t may be defined as

$$\hat{y}_t = \mathbf{1}(p_t > \xi), \quad (5)$$

where the conditional probability of recession p_t is obtained from a probit model, defined in Eq. (2). If p_t is larger than a threshold ξ , we get a signal forecast $\hat{y}_t = 1$ (i.e. recession), and vice versa $\hat{y}_t = 0$ if $p_t \leq \xi$.

In this paper, we employ the threshold $\xi = 0.5$ for SR, which can be seen as natural threshold in (5). However, this is not a fully objective selection, and in some previous studies lower values for ξ have also been used (see, e.g., Nyberg, 2010). In practice, the assigned threshold involves a trade-off between type I and II errors, i.e. the false positive and negative rates. The success ratio is important from the practical forecasters' point of view, especially if decisions are based on signals given by the model. However, as recession periods are uncommon compared to expansion periods, the success ratios of relatively uninformative models might turn out to be high. To test whether the value of the success ratio is higher than that obtained when the realized values y_t and the forecasts \hat{y}_t are independent, we employ the predictability test (PT) of Pesaran and Timmermann (2009).

Another way to measure the goodness-of-fit of binary dependent variable models is the Receiver Operating Characteristic (ROC) curve, which has become a commonly used method in economic applications in the recent years (see, e.g., Schularick and Taylor, 2012; Christiansen et al., 2014; Pönkä, 2016). The ROC curve is a mapping of the true positive rate

$$TP(\xi) = P_{t-1}(p_t > \xi | y_t = 1) \quad (6)$$

and the false positive rate

$$FP(\xi) = P_{t-1}(p_t > \xi | y_t = 0), \quad (7)$$

for all possible thresholds $0 \leq \xi \leq 1$, described as an increasing function in $[0, 1] \times [0, 1]$ space, with $TP(\xi)$ plotted on the Y-axis and $FP(\xi)$ on the X-axis. A ROC curve above the 45-degree line indicates forecast accuracy superior to a coin toss. Given that it takes into account all possible thresholds ξ , the ROC curve is a more robust method to evaluate the goodness-of-fit of a model than the success ratio.

The information in the ROC curve is typically summarized by the area under the ROC curve (AUC), which is the integral of the ROC curve between zero and one. Therefore, the AUC also gets values between 0 and 1, with the value of 0.5 corresponding a coin toss and the value 1 to a perfect forecast. Any improvement over the $AUC = 0.5$ indicates statistical predictability. We test the null hypothesis of $AUC = 0.5$ implying no predictability using standard techniques (see Hanley and McNeil, 1982).

A commonly used measure-of-fit for binary dependent variable models is the pseudo- R^2 of Estrella (1998). The measure is defined as

$$psR^2 = 1 - \left(\frac{\log L_u}{\log L_c} \right)^{-(2/T)\log L_c}, \quad (8)$$

where $\log L_u$ and $\log L_c$ are the maximum values of the unconstrained and constrained log-likelihood functions respectively, and T is the sample size. The pseudo- R^2 takes on values between 0 and 1, and can be interpreted in the same way as the coefficient of determination (R^2) in the usual linear predictive regression model. In Section 4, we report the adjusted form of (8) (see Estrella, 1998) that takes into account the trade-off between improvement in model fit and the use of additional estimated parameters.

3. Data

In this section, we discuss the data employed in this study. The sample used in the study is 1997–2017 and the data is quarterly.

3.1. The Russian business cycle

One of the key issues in terms of data is the selection of the business cycle chronology, as defined in Eq. (1). Unlike in the U.S., where the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER)² determines the official turning points, in Russia there is no such official chronology of recessions and expansions. However, there are a number of ways to determine the turning points based on data. Smirnov et al. (2017) recently established a monthly reference chronology for the Russian economic cycle from the early 1980s to mid-2015, using various seasonal adjustment methods and dating methods. In this paper, we define the turning points for business cycles using the Bry-Boschan (BB) algorithm (Bry and Boschan, 1971), which is a commonly used method in the literature. The dating is based on the algorithm used for seasonally adjusted quarterly real GDP data for the period 1997Q1–2017Q4. The sample length is determined by the availability of the predictive variables, described in the following Section. The resulting chronology is presented in Table 1 and was plotted with the Brent oil price in Fig. 1.

The BB algorithm finds three recession periods in the period 1997Q1–2017Q4. These findings are in line with those of Smirnov et al. (2017), who use monthly data in their reference chronology.

3.2. Predictive variables

The oil price variable selected for the study is the Brent Crude oil price in U.S. dollars, since it is a major global benchmark price for oil purchases. The main specification used is the quarterly change in prices (DOIL).³ As we are interested in studying the predictive ability of oil prices over and above other predictors, we employ a number of commonly used predictors of recessions as control variables. Several studies on other countries have suggested that financial variables are useful predictors of real activity and recessions (see, e.g., Stock and Watson, 2003). Among the most useful financial leading indicators are the term spread (TS) and stock returns (RET) (see, e.g., Estrella and Mishkin, 1998; Nyberg, 2010). Therefore, these predictors are obvious choices as additional predictors. The term spread is defined as the difference between the 10-year government bond yield and the 3-month interest rate.⁴ The stock return is defined as the logarithmic first difference on the stock market index.⁵

Along with these variables, also the short term interest rate has been employed as an explanatory variable in a number of studies (see, e.g., Wright, 2006; Pönkä, 2017). The findings of Wright (2006) suggest that a model including a short-term interest rate as a predictor alongside the term spread achieves a better in-sample fit in predicting U.S. recession periods. Sentiment variables, such as consumer confidence indices, are a particularly interesting group of variables, due to their forward-looking nature. Christiansen et al. (2014) find that the consumer confidence and purchasing managers' indices are useful predictors of US recession periods, even when combined with classic recession predictors and common factors based on a large panel of economic and financial variables. Based on these findings, we include the consumer confidence index (CCI) in our set of potential predictors.⁶

In Table 2, the predictive variables have been listed, along with the abbreviations and the starting points of the sample for each variable. Altogether, some of the data are already available from the beginning of 1997, so we are able to include the first recession period (1997Q4–1998Q3) in the sample. On the other hand, the term spread could only be used starting from 2001Q3 onwards.⁷

The correlations between the predictive variables are presented in Table 3. The highest correlations are found for the change in consumer confidence (DCCI). It is positively correlated with the term spread and the change in oil prices (DOIL) and negatively correlated with the change in the short term interest rate (DTM). The correlation between the oil price and term spread variables are also close to 0.5.

4. Results

In this Section, we present the main findings of our research. We first study the performance of the individual explanatory variables as predictors of the Russian business cycle. We allow each predictor to have a lag length between one to four quarters, as findings from previous literature has suggested that different variables have predictive ability at different lag lengths.

The findings in Table 4 illustrate that changes in oil prices do have predictive ability on future recession periods (using first and

² <http://www.nber.org/cycles/recessions.html>.

³ Source: U.S. Energy Information Administration, Crude Oil Prices: Brent – Europe [MCOILBRENTU], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/MCOILBRENTU>.

⁴ Source: OECD, 3-Month or 90-day Rates and Yields: Interbank Rates for the Russian Federation [IR3TIB01RUQ156N] and OECD, Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the Russian Federation [IRLTLT01RUQ156N], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org>.

⁵ Source: OECD, Total Share Prices for All Shares for the Russian Federation [SPASTT01RUM661N], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/SPASTT01RUM661N>.

⁶ Source: OECD (2018), Consumer confidence index (CCI) (indicator).

⁷ It is available starting from 1999Q1, but the ten-year government bond yields were so high in the first two years of the sample that using the data from that point onwards caused problems with the estimation of the model.

Table 1
Turning points for the Russian business cycle.

Peaks	Troughs
1997Q4	1998Q3
2008Q2	2009Q2
2014Q3	2016Q3

Table 2
Sample starting point for the leading indicators.

Variable	Abbreviation	Starting point
First difference of the Brent oil price	DOIL _t	1997Q1
First difference of the three-month interest rate	DTM _t	1997Q2
Logarithmic return of the stock index	RET _t	1998Q1
First difference of the consumer confidence index	DCCI _t	1999Q1
Term spread (10y bond yield minus the three-month interest rate)	TS _t	2001Q3

Notes: This table presents the predictive variables and their starting points.

Table 3
Correlations between employed predictive variables.

	DOIL _t	DTM _t	RET _t	DCCI _t	TS _t
DOIL _t	1	−0.449	0.441	0.577	0.482
DTM _t		1	−0.396	−0.519	−0.401
RET _t			1	0.362	0.301
DCCI _t				1	0.541
TS _t					1

Notes: This table presents the correlation coefficients between the employed predictive variables.

second lags). The coefficient is of the expected negative sign, implying that a fall in oil prices is related to an increased recession risk. However, it is the term spread that performs clearly the best as a predictor. The model including the first lag of the term spread yields an AUC of 0.969, whereas the one with the change in oil price yields an AUC of 0.743, which is also relatively high for a single predictor. The difference in fit is only partly explained by the shorter sample used for the term spread. In line with previous findings in the literature, the term spread has predictive ability even using longer lag lengths. The AUC for the model including the fourth lag of the term spread is 0.829.

The findings from the single predictor models were rather promising. Following the typical convention, we proceed by estimating multiple predictor models. Moreover, we estimate models including the oil price variable with each of the other predictors. We allow each variable to have a lag between one and four quarters, and report the best performing models in Table 5. In the case of the oil price variable, it turns out that either the second or the third lag of the variable is selected into the model.

In general, we find that models combining the oil price variable with classic recession predictors (Table 5) yield stronger results than single-predictor models (Table 4). Model 21 includes the oil price variable and the short term interest rate as predictors. The AUC is 0.797, which is higher than for the individual predictors in Table 4, but lower than for the other two predictor models (Models 22–24). In Models 21–23, the coefficient of the oil price variable is statistically significant, indicating that the oil price variable has predictive ability over and above the interest rate, stock return, and consumer confidence index variables. Model 24, including the term spread and the oil price, yields the highest AUC among the two-predictor models (0.974). This is higher than for the single-predictor model (Model 5) including the term spread. However, when used in combination with the term spread, the coefficient for the oil price variable is no longer statistically significant. The reason for this finding may lie in the relationship between these two variables. In Section 3.2, we noted that these variables are relatively highly correlated. The relationship between these two variables may be described as follows. A large reduction in oil prices leads to a weakening in the ruble.⁸ This in turn increases import prices, leading to higher inflation. As a reaction to higher inflation, short-term interest rates are raised. In extreme cases, the short term rates exceed the long term government bond yields, as happened both in 2008 and 2014.

In the last column of Table 5, we present the findings for the best performing three-variable model (Model 25). This model includes the short term interest rate in addition to the oil price and term spread variables. The findings indicate that increasing the number of predictive variables from two to three does not improve the model fit, as the AUC is lower than for the two-variable model (Model 24), and also the other goodness-of-fit measures imply a lower fit.

⁸ The literature on oil price shocks and exchange rates is well established. See, e.g., Chen and Chen (2007) for research on G7 countries, Ji et al. (2015) for BRICS countries, Volkov and Yuhn (2016) for five major oil-exporting countries, and Mensah et al. (2017) for oil dependent economies.

Table 4
In-sample results for single-predictor probit models.

	Variable	Coeff.	adj.psR ²	BIC	SR	AUC
<i>First lags</i>						
1	DOIL _{t-1}	-0.052**	0.101	39.845	0.841	0.743***
2	DTM _{t-1}	0.169***	0.092	40.185	0.841	0.703***
3	RET _{t-1}	-0.022***	0.051	39.812	0.810*	0.683**
4	DCCI _{t-1}	-0.101***	0.107	34.022	0.880	0.689**
5	TS _{t-1}	-0.806***	0.557	18.156	0.908	0.969***
<i>Second lags</i>						
6	DOIL _{t-2}	-0.048*	0.087	40.193	0.840	0.720***
7	DTM _{t-2}	0.091*	0.015	43.033	0.815	0.613*
8	RET _{t-2}	-0.023**	0.055	37.966	0.821	0.728***
9	DCCI _{t-2}	-0.069***	0.041	36.211	0.838	0.649**
10	TS _{t-2}	-0.240**	0.204	29.108	0.828	0.903***
<i>Third lags</i>						
11	DOIL _{t-3}	-0.013	Neg.	43.980	0.800	0.628*
12	DTM _{t-3}	-0.012	Neg.	44.385	0.800	0.473
13	RET _{t-3}	-0.008	Neg.	38.896	0.831	0.623*
14	DCCI _{t-3}	-0.043	Neg.	37.514	0.822	0.642*
15	TS _{t-3}	-0.154	0.085	32.602	0.778**	0.858***
<i>Fourth lags</i>						
16	DOIL _{t-4}	-0.003	Neg.	42.746	0.810	0.517
17	DTM _{t-4}	0.010	Neg.	42.747	0.810	0.570
18	RET _{t-4}	-0.005	Neg.	38.990	0.829	0.600
19	DCCI _{t-4}	-0.047	0.004	37.121	0.806	0.673**
20	TS _{t-4}	-0.143	0.072	32.791	0.774	0.829***

Notes: This table presents the findings from single-predictor probit models for Russian recessions. The table includes findings for the oil price and control variables. Robust standard errors are given in brackets (see Kauppi and Saikkonen, 2008). The goodness-of-fit measures are described in detail in Section 2.

* Denotes the statistical significance of the estimated coefficients and the AUC at 10% significance level.

** Denotes the statistical significance of the estimated coefficients and the AUC at 5% significance level.

*** Denotes the statistical significance of the estimated coefficients and the AUC at 1% significance level.

Table 5
Estimation results for in-sample predictive models.

Variable	21	22	23	24	25
DOIL _{t-2}		-0.067** (0.031)	-0.046* (0.027)		
DOIL _{t-3}	-0.054*** (0.021)			0.024 (0.016)	-0.018 (0.021)
DTM _{t-1}	0.307*** (0.064)				0.264 (0.168)
RET _{t-1}		-0.051*** (0.016)			
DCCI _{t-3}			-0.041 (0.033)		
TS _{t-1}				-0.723*** (0.168)	-0.544*** (0.139)
CONST	-1.036*** (0.276)	-0.871*** (0.293)	-0.948*** (0.279)	-0.227 (0.259)	-0.111 (0.273)
adj.psR ²	0.214	0.213	0.106	0.327	0.261
BIC	35.345	32.107	35.275	26.909	30.450
SR	0.835	0.882**	0.847	0.857***	0.823***
AUC	0.797**	0.812**	0.812***	0.974***	0.973***

Notes: This table presents the findings from probit models for Russian recessions.

* Denotes the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 10% significance level.

** Denotes the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 5% significance level.

*** Denotes the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 1% significance level.

See also notes to Table 4.

Table 6
In-sample results from autoregressive probit models.

Variable	AR21	AR22	AR23	AR24	AR25
DOIL _{t-2}		-0.024 (0.017)	-0.029 (0.045)		
DOIL _{t-3}	-0.017 (0.021)			0.029 (0.034)	-0.007 (0.028)
DTM _{t-1}	0.310*** (0.091)				0.232 (0.172)
RET _{t-1}		-0.025*** (0.010)			
DCCI _{t-3}			-0.037 (0.034)		
TS _{t-1}				-0.526*** (0.068)	-0.362*** (0.083)
π_{t-1}	0.827*** (0.099)	0.783*** (0.090)	0.487 (0.938)	0.486*** (0.042)	0.490 (0.052)
CONST	-0.183 (0.132)	-0.132 (0.108)	-0.489 (0.903)	-0.371*** (0.144)	-0.178 (0.112)
adj.psR ²	0.412	0.216	0.086	0.300	0.294
BIC	31.140	35.493	37.797	29.446	31.190
SR	0.887***	0.821	0.836	0.857*	0.887***
AUC	0.815***	0.847***	0.782***	0.952***	0.965***

Notes: This table presents the findings from autoregressive probit models for Russian recessions.

* Denotes the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 10% significance level.

**Denotes the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 5% significance level.

*** Denotes the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) (PT) predictability test for the success ratio, and the AUC at 1% significance levels, respectively.

See also notes to Table 4.

4.1. In-sample findings from autoregressive models

As an extension to the conventional static probit model, we employ the autoregressive specification described in Eq. (4). The findings from autoregressive probit models are presented in Table 6 and they indicate that the autoregressive extension is not particularly useful in our application. For some of the models, the autoregressive extension does improve the model performance (Models AR21 and AR22) compared to their static counterparts in Table 5. However, this is not the case for the other models (AR23–AR25). The best performing autoregressive model is Model AR25, with an AUC of 0.965, which is lower compared to 0.973 of Model 25.

4.2. Out-of-sample findings

As previous forecasting literature has shown, good in-sample fit does not necessarily imply good out-of-sample performance. Therefore, in this section, we will examine the pseudo out-of-sample forecasting performance of our models. We use an expanding window forecasting approach with estimation samples ranging from 2001Q3–2009Q4 to 2001Q3–2017Q3, and report the results of one- and two-quarter-ahead forecasting horizons.⁹ Therefore, in our forecasting sample (2010Q1–2017Q4), there is only one recession. This limitation is due to the small number of recessions in the full sample, as for each estimation sample we need at least one recession period. For this reason, the out-of-sample findings should mainly be seen as illustrative (Table 7).

The findings indicate that the models including the term spread (TS and Model 24) perform best among the models in one-quarter-ahead forecasts, with out-of-sample AUCs of 0.932 for both models. Model 23, including the oil price and consumer confidence variables, also performs relatively well (AUC = 0.918). In the case of two-quarter-ahead forecasts, the single predictor model including the oil price variable performs the best, yielding an AUC of 0.894. Overall, the findings are in line with the in-sample ones, and confirm that oil prices and the term spread are valuable indicators of future recessions in Russia.

5. Conclusion

In this paper, we have studied the role of oil prices on Russian business cycle fluctuations. The findings indicate that changes in oil prices are a valuable indicator of future recession periods. However, the term spread, defined as the difference between the ten-year government bond and the three-month interest rate, yields even stronger results based on the area under the ROC curve (AUC), which

⁹ This selection is based on the sample length available for the term spread.

Table 7

Out-of-sample results for models including credit variables and classic predictors.

Model	DOIL	DTM	RET	DCCI	TS	21	22	23	24
<i>Forecast horizon: 1 quarter</i>									
SR	0.813	0.781	0.438	0.781	0.875	0.750	0.563	0.719	0.813
AUC	0.787***	0.792***	0.237	0.783***	0.932***	0.778***	0.662*	0.918***	0.932***
<i>Forecast horizon: 2 quarters</i>									
SR	0.719	0.781	0.563	0.719	0.719	0.688	0.469	0.719	0.688
AUC	0.894***	0.758***	0.522	0.783***	0.831***	0.676**	0.261	0.836***	0.609

Notes: This table presents the one-to-four-quarter-ahead forecasting results from static probit models for Russian recession periods. See also the notes to Table 4.

has been the main goodness-of-fit measure in this paper. This result shows that the previous findings highlighting the usefulness of the term spread as a leading indicator of recession periods also apply for Russia.

In our in-sample estimations, we follow the strategy used by Christiansen et al. (2014) and Pönkä (2017), and test the predictive ability of our variable of interest over and above classic recession predictors. Overall, we find that models combining the changes in oil prices with classic recession predictors improve the in-sample performance of the models. This underscores the importance of oil prices for the Russian economy. Although, when used in combination with the term spread, the predictive ability of the oil price is no longer suggested by the findings of our models, the relationship between these variables provides a logical explanation to this finding, as monetary policy reacts to shocks in oil prices.

Furthermore, we test the robustness of our in-sample findings in a pseudo out-of-sample exercise, and find that the in-sample findings are generally confirmed by the out-of-sample forecasts. Moreover, models including the term spread perform the best in one-quarter-ahead forecasts, whereas a model including the change in oil prices, yields the highest AUC in two-quarter-ahead forecasts.

As an extension to our main analysis, we have experimented with an autoregressive extension to the conventional static probit model. It turns out that the more parsimonious static model generally outperforms the autoregressive model in our application.

The findings of this paper could be extended in a number of ways. One possible extension would be the use of a larger set of variables and possibly also common factors based on a large panel of financial and macroeconomic variables, in the lines of Christiansen et al. (2014) and Pönkä (2017). Another possible extension would be to study the issue using different definitions of oil price shocks, such as the nonlinear oil price index (NOPI) of Hamilton (1996). Finally, the findings of this paper could be complemented by studying the predictive ability of oil prices on the direction of Russian stock market returns, in a similar way as Pönkä (2016) did for eleven developed countries.

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